Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 3 (2014) 109 – 118

Transportation Research Procedia

www.elsevier.com/locate/procedia

17th Meeting of the EURO Working Group on Transportation, EWGT2014, 2-4 July 2014, Sevilla, Spain

Geographic, social-cultural and modal usage determinants of activity space: a case study of EU Institutions in Luxembourg and Strasbourg

Tai-Yu Ma[a]*, Philippe Gerber[b], Samuel Carpentier[c], Sylvain Klein[d]

[a,b,d]CEPS/INSTEAD, 3, avenue de la fonte L-4364 Esch-sur-Alzette, Grand–Duché de Luxembourg
[c] Aix-Marseille Université, CNRS, ESPACE UMR 7300, 29, avenue Robert Schuman F-13621 Aix-en-Provence cedex 1, France

Abstract

Human activity space is well-known to be related to his geographic, social-culture position, build environment and modal usage. The interrelationships between these observed and unobserved factors shape a person's spatial usage and visited activity locations. This study applies the structural equation modeling approach to identify the direct and indirect effects of these factors on the size of an individual's activity space. The data is based on the recent mobility survey for three European Institutions: the European Investment Bank and the Court of Justice of the European Union in Luxembourg city and the Council of Europe in Strasbourg (France). The empirical analysis shows that the size of a person's activity space is mainly explained by the build environment and less related to the socio-demographic variable when a workplace is controlled. The suggested structural equation model provides a flexible framework to investigate empirical effects of these factors on the activity space.

Selection and peer-review under responsibility of the Scientific Committee of EWGT2014

Keywords: Activity space; travel behavior; structural equation model; EU Institutions

1. Introduction

It has been recognized that human activity space is related to his geographic location, travel behavior and socio-demographic context (Dijst, 1999). However, the structural relationship between these factors is still less

* Corresponding author. Tel.: +352 585855308; fax: +352 585855700.
E-mail address: tai-yu.ma@ceps.lu

Selection and peer-review under responsibility of the Scientific Committee of EWGT2014
doi:10.1016/j.trpro.2014.10.096

investigated due to data availability in terms of person's activity locations. In the past, different approaches have been applied for analyzing a person's activity space and its relationship with spatial and socio-demographic attributes (Schönfelder and Axhausen, 2003). Dijst (1999) conducted an exploratory analysis of the typology of an individual's activity space and proposed a theoretical framework to explain different activity space concepts. He suggested that three types of action (activity) space can be distinguished: potential, actual and perceived. The potential action space concerns a set of potential activity places where an individual may visit during a period of time. The actual activity space concerns the area or places that an individual has already visited during a period of time, which reveals an individual's actual living space. The perceived activity space is related to an individual's spatial cognition about activity places. The author suggested that a person's residential location and his workplace are the two main anchor points (bases) which shape the activity space. Four determinants are proposed to explain the activity space: distance between the bases of the activity space, available time interval, travel time ratio and the speed of travel (transport modes) (Hagerstrand, 1970). Although these factors influence the size of the activity space, it still lacks a deeper insight in how socio-demographic, build environment, travel behavior and cognitive/perception influence the reached area of a person's daily activity. For this issue, Schönfelder and Axhausen (2003) investigated the suitability of different activity space measurements: confidence ellipse, kernel density estimates and shortest paths networks. They found that the size of a person's activity space is mainly determined by the overall number of unique locations visited by an individual. The authors analyzed the influence of socio-demographic characteristics by a generalized linear model and found that the socio-demographic characteristics have lesser influence on the size of a person's activity space, compared to the overall number of unique locations visited. In this study, we focus on a person's actual activity space (call simply activity space hereafter).

To investigate the complex casualty between a set of endogenous and exogenous variables, the structural equation model (SEM) is very adequate for such a research purpose (Bollen, 1989; Kline, 2005). The SEM is a flexible casual relationship identifying approach which can simultaneously estimate the interrelationships among a set of endogenous and exogenous variables under a hypothesized relationship. This approach has been widely applied in marketing (Baumgartner and Homburg, 1996), psychology (MacCallum and Austin, 2000) and also in transportation science (Golob, 2003). The SEM has been applied to investigate the interrelationships between travel behavior and others factors such as: (1) car ownership and built environment (Van Acker and Witlox, 2010; Simma and Axhausen, 2003), (2) activity demand (Lu and Pas, 1999), (3) attitudes and perceptions (Ory and Mokhtarian, 2009).

In this study, a structural equation model with latent variables is suggested to analyze the effects of spatial, socio-cultural and modal usage on the size of a person's activity space. A theoretical framework for modeling the activity space is proposed and examined by our empirical survey data. The proposed approach provides a flexible tool to investigate the effects of different exogenous and endogenous latent factors on the size of activity space. The organization of this study is as follows. Section 2 suggests a conceptual framework for modeling activity space and recalls the basic concept of the structural equation model. Section 3 reports the descriptive statistics of the survey data and the geocoding method of a person's activity locations. Section 4 presents the estimation results and its interpretation. Finally, a conclusion is drawn and future extensions are discussed.

2. Conceptual framework and the structural equation model

We first review the key determinants of a person's activity space and propose a conceptual framework for modeling a person's activity space in terms of these key determinants. It follows a short description of the SEM model, model assumptions and the estimation methods.

2.1. Conceptual framework of modeling a person's activity space

Based on our literature review, we can distinguish four types of determinants to explain an individual's activity space: geographical, socio-demographic, modal usage and attributes towards transport modal usage.

- **Geographical**: a high-density build environment provides generally a better accessibility to different activity places, thus negatively associated with the size of a person's activity space (Van Wee et al. 2002; Harding et al. 2012). The distance between a person's residential location and his workplace is positively related to the size of his activity space (Dijst, 1999; Schönfelder and Axhausen, 2003; Carpentier and Gerber, 2009; Carpentier, 2012). The degree of urbanization and amenities in the neighborhood influence an individual's traveled distance to reached places. The space-time constraint shapes a person's available time to his reached area and influences his destination choice decisions (Hägerstrand, 1970).

- **Socio-demographic**: a person's activity space is related to his available time for travel and to his lifecycle stage. An individual's work place is directly related to his employment status (Dijst, 1999). The presence of children explains an individual's participations for certain activities such as accompanying children to school or to leisure activities, etc. Other factors such as gender, household income and marital status have different effects on an individual's activity participations and location choices (Schönfelder and Axhausen, 2003; Simma and Axhausen, 2003).
- **Mode use**: It has been shown that the built environment and travel behavior is correlated. People living in high-density area are associated with lower car ownership and car use, but with higher public transport uses / walking (Van Acker and Witlox, 2010). Mode uses are related to the destination choices of activity and thus explain the size of a person's activity space (Sinha, 2003; Gori et al. 2012).
- **Attitudinal and cognitive**: an individual's activity space is determined both by his experienced space-time behavior and by the knowledge about his activity locations (spatial cognition space) (Schönfelder, 2001). Moreover, a person's mode choice is associated with his attitudinal preferences and indirectly influences his location choices of activity (Ory and Mokhtarian 2009).

The above empirical findings suggest four categories of key variables: (1) *socio-demographic*: age, gender, marital status, number of children, flexible work hours, education level, household income, (2) *geographical or urban environment*: distance between a household location and a city center, distance between a household location and a workplace, distance to the nearest station of public transport, population density at residence location, unobserved city-specific factor, etc.; (3) *attitudinal*: attitudes towards car and towards public transport, spatial cognition and knowledge; (4) *travel behavior*: modal usage, car ownership and season ticket ownership.

As direct modeling the interrelationship between these variables and its influences on the activity space might cause the model identification issue (a large number of parameters to be estimated) and also the difficulty in the result explanation. Moreover, due to the presence of binary or discrete variables, the multivariate normality assumption of endogenous variables cannot be hold for the maximum likelihood estimation method (Kline, 2005). Although the method of weighted least squares for arbitrary distributions (WLS) allows us to overcome this issue, several thousand samples might be a minimum requirement to obtain expected statistical properties (SAS Institute Inc., 2013). As our sampled size (individuals) is far lower than required to apply this method, we propose an alternative way by incorporating a set of latent variables to characterize these key variables in a measurement model and to model the direct and indirect effects of these latent variables in a path model on our target variable (the size of activity space). The proposed hypothesized causality relationship is illustrated in Fig. 1. Note that our interest is to identify the direct and indirect effects of the latent variables on the activity space and the factor loadings of each latent variable. The top-left of Fig. 1 reports a conceptual relationship to explain a person's activity space based on the aforementioned empirical findings. The symbols in Fig. 1 designate the plausible causal associations between the endogenous and exogenous variables. A directional arrow reveals a plausible causal relationship / direct effect. The symbol means an unexplained association. An ellipse represents a latent factor characterized by some exogenous variables. A rectangle is referred to as an exogenous variable. The hypothesized relationship describes that the activity space is influenced directly by a person's socio-demographic characteristics, build environment and modal usage. Attitudinal factor plays an intermediate role between the socio-demographic characteristics and the modal usage. From a theoretical point of view, there might be a strong/weak association between each pair of the latent factors. For each latent variable, it is characterized by a set of exogenous observed variables.

Note that the latent attitudes towards different modes of transport are not included in this study. They will be the target of future investigations. As a result, three models, ordered by increasing interrelationships between the latent variables, are derived from the full model with the same available exogenous variables (Fig. 1). Model 1 combines the build environment and modal usage as a latent factor. Model 2 distinguishes three latent variables: the socio-demographic, build environment and modal usage, and assumes that each latent variable has a direct effect on a person's activity space. The modal usage is influenced by its build environment. Model 3 extends model 2 by adding an association between the socio-demographic characteristics and the modal usage as well as an association between the socio-demographic characteristics and the build environment. Each model will be estimated separately and compared based on the model-fit statistics.

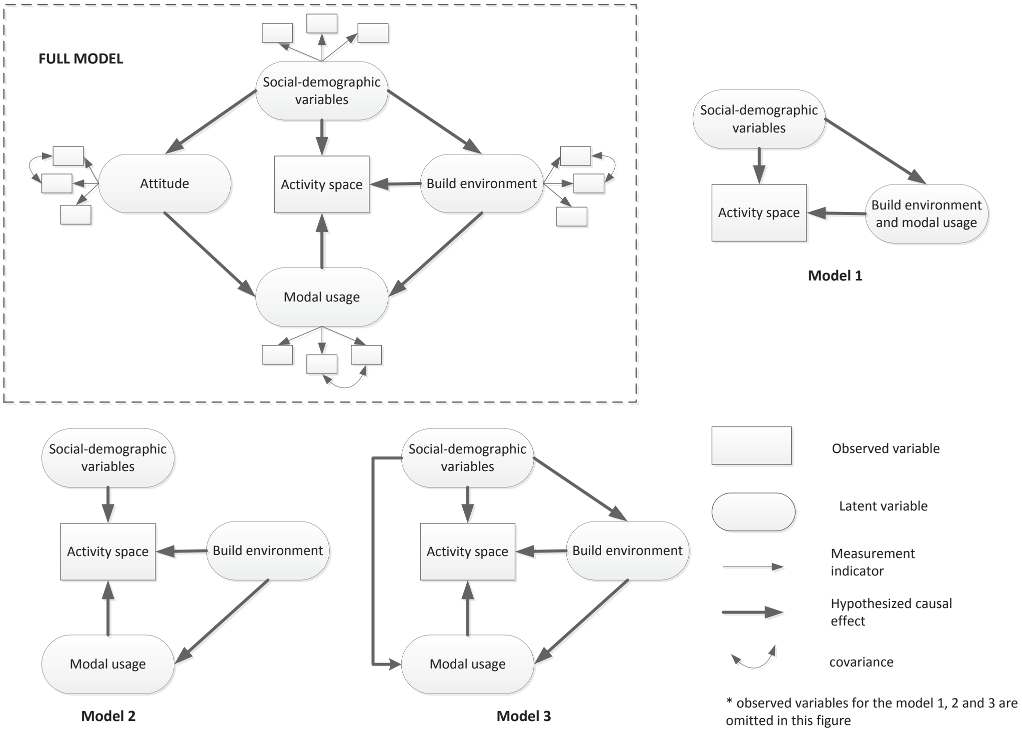

Fig. 1. Structural relations among exogenous, endogenous variables and a person's activity space

2.2. Structural equation modeling approach

The SEM is composed of a system of equations which represent the relationships between endogenous and exogenous variables (Bollen, 1989; Kline, 2005). A latent variable is defined as an unobserved variable which can be measured or characterized by a set of exogenous variables (indicators). Latent variables can be incorporated in the hypothesized causal relationships to measure direct and indirect causal effects of observed and unobserved variables. The general SEM comprises of two components (Kaplan, 2001): (1) a *path model* which captures the casual relationships of endogenous and exogenous variables and (2) a *measurement model* which links latent variables with a set of observable measurements. The path model (structural part) is defined as

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta} \tag{1}$$

where $\boldsymbol{\eta}$ and $\boldsymbol{\xi}$ is a vector of endogenous and exogenous variables, respectively. $\mathbf{B}$ and $\boldsymbol{\Gamma}$ are the corresponding matrices of regression coefficients to be estimated. The latent variables are linked to a set of measurements defined as:

$$\mathbf{y} = \boldsymbol{\Lambda}_y\boldsymbol{\eta} + \boldsymbol{\varepsilon} \tag{2}$$

$$\mathbf{x} = \boldsymbol{\Lambda}_x\boldsymbol{\xi} + \boldsymbol{\delta} \tag{3}$$

where $\mathbf{\Lambda}_y$ and $\mathbf{\Lambda}_x$ are the matrices of the factor loadings for endogenous and exogenous variables in the measurement model, respectively. $\boldsymbol{\zeta}, \boldsymbol{\varepsilon}, \boldsymbol{\delta}$ are the variance and covariance matrices. The estimation of the SEM model is based on minimization of the differences between the observed and estimated variance-covariance matrices. A most commonly used estimation method is the Maximum Likelihood (ML) method when the dependent variable is continuous. This method requires a multivariate normal distribution of the endogenous variables. The reader is referred to Bollen (1989) and Kline (2005) for a more detailed description.

3. Data collection and geocoding of activity addresses

The data is based on the recent mobility, city perceptions and activity location survey for the employees of three EU Institutions in Luxembourg (European Investment Bank and Court of Justice of the European Union) and Strasbourg, France (the Council of Europe). The survey was conducted during November-December 2012. The survey collected the geographical information at a level of street or quarter about an individual's residence, workplace and visiting places of activities in the month[†] before the date of the survey. The respondents were asked to report the activities pursued among a list of activity purposes: shopping for maintenance, shopping, social activity, cultural-sportive activity, visiting friends, visiting family members, accompanying children to school, accompanying children for activities, go to a restaurant, go to a bar, cinema, cultural activities, service activities (see a doctor, go for a bank, etc.). As regards the degrees of resolution of the reported activity addresses, we have 74.5% and 55.3% of the reported non-work activity addresses with a resolution at address/quarter/street levels for the samples in Luxembourg and Strasbourg, respectively. The rest of the addresses are at a resolution of commune. As regards for the geocoding of the communes, the city hall or the centroid of build area is used for the geocoding.

As regards the measurement of an activity space, different methods have been suggested (Schönfelder and Axhausen, 2003; Rai et al. 2007). One of the most widely applied methods is the standard deviational ellipse which calculates an elliptical shape based on the geographical x-y coordinates to feature the spatial distribution of the reported activity locations. This method computes the standard deviations of x- and y- coordinates and generates an ellipse based on the deviations. The reader is referred for Bachi (1962) and Miranda-Moreno et al. (2010) for a more detailed description. We use the directional distribution tool in ESRI's ArcGIS to compute the standard deviational ellipses of activity spaces.

After eliminating the outliers and samples with missing values, there are totally 388 samples. Descriptive statistics of the data is reported in Table 1. The average size of activity space in Luxembourg is 153.9 km^2, which is much greater than that in Strasbourg (77.1 km^2). As regards the socio-demographic characteristics, the age in average is about 42 and 44 years in Luxembourg and Strasbourg, respectively. Most respondents are females in Strasbourg (77%) compared to that in Luxembourg (55%). The average number of children in the household is around 0.9 in both cities. Most respondents in both cities have flexible work hours and living in couple. The average distance between a person's household location and his workplace is similar between these two cities (around 10 km). The population density of commune where locates the household in Strasbourg is 2214.2 hab./km^2, much higher than that in Luxembourg (1039 hab./km^2). The car ownership for the respondents is similar in both cities, but the season-ticket ownership is much higher in Luxembourg compared to that in Strasbourg.

† As mentioned by Schönfelder and Axhausen (2003), the size of a person's activity space can be estimated over a longer time horizon.

Table 1. Summary statistics of socio-demographic, built environment and modal commitment variables

Variable	Description	Luxembourg	Strasbourg
		Mean (S.D)	Mean (S.D)
Sample size (N)		299	114
Size of activity space (km2)	Size of a person's activity space, measured by a standard deviational ellipse (km^2)	153.9 (281.8)	77.1 (160.4)
Socio-demographic variables			
Male	1 if male, 0 female (% of 1)	0.45	0.23
Age		42.12 (8.5)	44.21 (8.0)
N_children	Number of young children less than 15 years of age in the household	0.92(1.1)	0.90(1.0)
Couple	1 if the individual lives in couple, 0 otherwise (% of 1)	0.78	0.80
Flex_time	1 if individual has flexible work hours, 0 otherwise (% of 1)	0.83	0.90
Built environment			
Dist_station	Distance from a person's home to nearest railway station (km)	2.38(3.3)	1.95(1.7)
Dist_home_work	Distance between a person's household location and his workplace (km)	10.85(12.8)	9.74 (13.6)
Strasbourg_city	Indicator for the city-specific effect	0.0	1.0
Density	Population density by commune (hab./km^2)	1039.0 (748.0)	2214.2 (1524.1)
Modal commitments characteristics			
Car_ownership	1 if there is at least one car in the household, 0 otherwise (% of 1)	0.93	0.93
Season_ticket	1 if the individual has a season ticket for public transport, 0 otherwise (% of 1)	0.67	0.21

4. Empirical result

The SEM model is estimated by the SAS CALIS procedure. The model estimation process is guided by a two-step estimation procedure (Kline, 2005, p. 267). At the first step, an acceptable measurement model is identified based on a conceptual relationship by incorporating relevant exogenous variables to capture the associations between latent variables and its measurements. The second step consists of improving the acceptable model at the first step by fitting some alternative models with different structures and association assumptions. A better structural model can be then selected based on the model fit statistics. Before the model estimation, a data filtering process is conducted to delete the outliers and highly correlated exogenous variables. Our data has only one observed endogenous variable (the size of activity space). Its skewness and kurtosis is 3.44 and 13.72, respectively, which indicates a moderate non-normality and has a moderate influence on the estimation results based on the ML estimation method. Note that one can apply Box-Cox transformations on the size of activity space for rectify this issue (Kline, 2005).

4.1. Model fit statistics

The different goodness-of-fit statistics of the three models can be found in Table 2. The χ^2 statistic measures the discrepancy between the sample and model covariance matrices. This statistic is used for overall model fit assessment. However as Baumgartner and Homburg (1996) stated, the χ^2 statistic is not robust when the multivariate normality assumption is violated. For this issue, different overall goodness-of-fit criteria are proposed in Table 2. The reader is referred to Baumgartner and Homburg (1996) and Iacobucci (2010) for more detailed discussions about these fit statistics. As these models are nested, we can compare them directly by their χ^2 statistic improvement. The χ^2 statistic difference test shows that model 1 and model 2 are statistically indifferent. However, the model 3 significantly improves the model 2 (p-value <0.001). Its model-fit statistics satisfy related critical fit indices. Hence the model 3 is our retained model for further discussions in the next section. Note that R^2 is particularly useful to assess explained variance of endogenous variables by each structural equation model. We report these R^2 in Table 3.

Table 2 Model fit statistics and the criteria for goodness-of-fit

Model-fit statistics	Critical value of goodness-of-fit[1]	Model 1	Model 2	Model 3
N		388	388	388
Df		32	29	28
χ^2	Better fit for smaller values	101.635	96.2151	**77.461**
χ^2 /df	<=3.0	3.18	3.01	**2.42**
Pr > Chi-Square	<=0.05	<.0001	<.0001	**<.0001**
Jöreskog-Sörbom Goodness of Fit Index (CFI)	>=0.95	0.9496	0.9532	**0.9634**
RMSEA (root mean square error of approximation)	<=0.06	0.075	0.0774	**0.0676**
Standardized root mean square residual (SRMR)	<=0.09	0.0669	0.0652	**0.0533**

Remark: the critical values of goodness-of-fit statistics are drawn from Lei and Wu (2007), Kline (2005) and Iacobucci (2010).

4.2. Parameter estimates, direct and indirect effects

The estimation results of the structural coefficients and loading factors of model 3 are shown in Table 3 and Fig. 2. We first discuss the estimation results of the measurement model. Note that the coefficients in the measurement model as well as those in the path model are explained as regression coefficients on its dependent variable. A square multiple correlation (R^2) represents the percentage of variance explained by a predictor (covariate). All observed exogenous variables are statistically significant except the season-ticket ownership. For socio-demographic measurements, couple and number of children in the household are two main determinants of the socio-demographic latent variable. These two measurements have negative effects on the score of the socio-demographic latent variable (F1). Together with the positive effect of F1 on the size of activity space, we can obtain its negative effects on the size of activity space. The result indicates that couple with children has smaller activity space compared with single without children. For the latent variable of build environment (F2), home-work distance and population density are two main measurements which explain 88% variations of F2. The build environment has a prominent effect of activity space. Combined with its factor loadings related to its measurements, we found that higher home-work distance, larger the size of activity space. By contrast, higher the population density of commune of the household location is, smaller the size of activity space is observed. The result indicates that the employees' activity space is highly related to his living neighborhood and their home-work distances. The two anchoring points shape an employee's daily reached activity area. This result is consistent with the empirical findings of the previous study (Schönfelder and Axhausen, 2003). As regards the latent variable of modal usage (F3), car ownership is the main determinant which accounts for 32.8% of variation of F3. Indeed, the season ticket ownership may influence a user's mode choice decision, resulting in different travel distance and the size of activity space (Schönfelder and Axhausen, 2003). However, our empirical result indicates that the influence of the season ticket ownership on the size of activity space is not significant. This might be explained by the fact that the season ticket is mainly used for commuting trips between an employee's residential location and his working place located in one of these EU Institutions. The size of individual's activity space for each employee is mainly determined by his car uses for other types of activities. Unanalyzed variation of F3 is still relatively high and need to be further reduced by introducing other relevant measurements such as the percentage of car-use trips, etc. Jointly with the negative effect of the modal usage on the size of activity space, we found higher the car ownership is, smaller the size of activity space. However, its effect needs to be further confirmed by introducing other measurements.

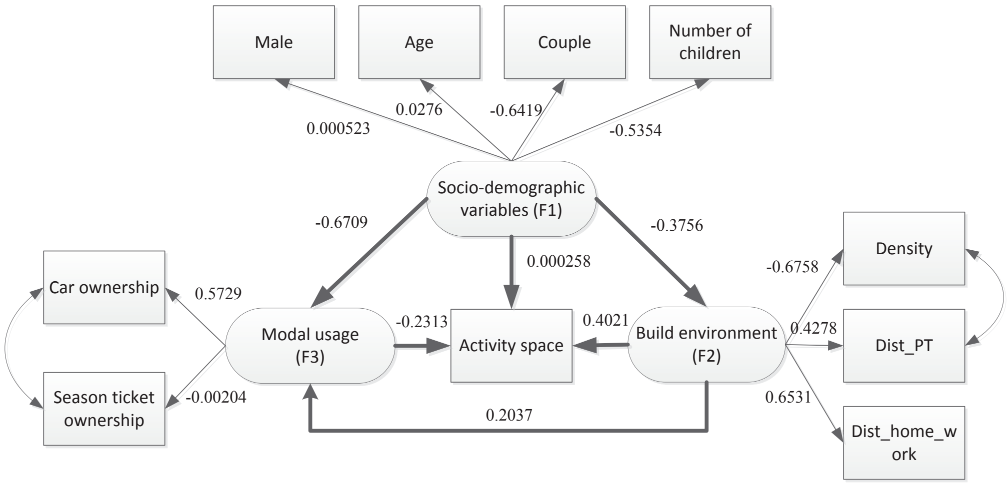

Fig. 2. Maximum likelihood estimates of structural equation model of a person's activity space

Table 3 Parameter and standard error estimates of structural equation model

Variable	Standardized Coef.	Std.	t-value	Squared Multiple Correlations (R^2)
Socio-demographic variables (F1)				
Male	0.000523	0.000019	27.8209	2.74E-07
Age	0.0276	0.00114	24.3019	0.000765
N_children	-0.5354	0.0472	-11.3558	0.2867
Couple	-0.6419	0.0621	-10.3418	0.412
Built environment (F2)				
Dist_station	0.4278	0.0553	7.7366	0.183
Dist_home_work	0.6531	0.0466	14.0168	0.4266
Density	-0.6758	0.0268	-25.2405	0.4568
F1->F2	-0.3756	0.0728	-5.1574	-
Modal usage (F3)				
Car_ownership	0.5729	0.14	4.0913	0.3282
Season_ticket	-0.00204	0.0836	-0.0244	4.16E-06
F1->F3	-0.6709	0.1774	-3.7808	-
F2->F3	0.2037	0.127	1.6038	-
F1->activity space	0.000258	7.29E-06	35.4626	-
F2-> activity space	0.4021	0.0759	5.295	-
F3-> activity space	-0.2313	0.0869	-2.6622	-

Table 4 reports the direct, indirect and total effects of the latent variables on the size of activity space. An indirect effect is calculated as the multiplication of coefficients on a causal path. A total effect is the summation of its direct and indirect effects. The result indicates that the build environment has a most significant direct effect (0.40210) compared to the modal usage (-0.2313) on the size of activity space. The socio-demographic variables have little impact on a person's activity space.

Table 4 Direct, indirect and total effects of latent factors on the size of activity space

	Direct effect	Indirect effect	Total effect
Socio-demographic variables (F1)	0.000258	F1 → F2 → AS = -0.15103 F1 → F3 → AS = -0.15517 F1 → F2 → F3 → AS = -0.01769	0.022105
Built environment (F2)	0.40210	F2 → F3 → AS = -0.04712	0.35498
Modal usage (F3)	-0.23130		-0.23130

Remark: 1.AS means activity space; 2. An indirect effect is computed as the multiplication of path coefficients. For example, F1 → F2 → AS = -0.3756*0.4021=-0.1510; 3. Total effect is the summation of the direct and indirect effects on AS.

5. Conclusions

In this study, we propose a structural equation model for investigating the effects of socio-demographic, building environment and modal usage on the size of a person's activity space. The proposed approach provides a flexible framework to investigate direct and indirect effects of these factors on the activity space. The results suggest that build environment related to home-work distance and population density of commune of household location is most relevant determinants of the size of the activity space when a person's workplace is controlled. The socio-demographic characteristics have relatively low effects on the size of activity space.

Further study might be desired for further consolidating the empirical findings. Possible directions include the incorporations of: (1) an attitudinal or spatial perception latent factor, (2) measurements related to the modal usage of a person's activity space and/or a relevant accessibility measurement. Moreover, a deeper investigation of the spatial distribution of household locations with related to their activity spaces is also expected to improve our understanding in the differences of activity spaces between the employees in these two areas.

Acknowledgements

The author thanks sincerely the support of Fonds National de la Recherche Luxembourg for the ACROSS project (Assessing the Socio-Cultural Effects on Mobility Behaviours in Cross-Border Areas), CORE 2010 (SR/783207). Special thanks to Ms. Bérengère Darud and Ms. Lauriana G. Dragut for their technical support in the survey database construction and geocoding of activity addresses. We acknowledge M. Marc Schneider for his technical support in activity space computation.

References

Bachi, R., 1962. standard distance measures and related methods for spatial analysis. Papers in Regional Science 10, 83–132. doi: 10.1111/j.1435-5597.1962.tb00872.x

Baumgartner, H., Homburg, C., 1996. Applications of structural equation modeling in marketing and consumer research: A review. International Journal of Research in Marketing 13, 139-161.

Bollen, K.A., 1989. Structural Equations with Latent Variables. Wiley, New York.

Carpentier S., 2012. Cross-Border Local Mobility between Luxembourg and the Walloon Region: an Overview. European Journal of Transport and Infrastructure Research 12(2), 198-210.

Carpentier S., Gerber P., 2009. De la mobilité résidentielle à la recomposition des espaces de la vie quotidienne. Recherche Transports Sécurité 25(102), 61-72.

Dijst, M., 1999. Action space as planning concept in spatial planning. Journal of Housing and the Built Environment 14(2), 163-182.

Golob, T.F., 2003. Structural equation modeling for travel behavior research. Transportation Research Part B 37, 1–25

Gori, S., Nigro, M., Petrelli, M., 2012. The Impact of Land Use characteristics for Sustainable Mobility: the case study of Rome. European transport research review 4(3), 153-166.

Hägerstrand, T., 1970. What about people in regional science?, Paper in Ninth European Congress of the Regional Science Association.

Harding, C., Patterson, Z., Miranda-Moreno, L. F., Zahabi, S. A., 2012. Modeling the Effect of Land Use on Activity Spaces. Transportation Research Record 2323, 67-74.

Iacobucci, D., 2010. Structural equations modeling: Fit Indices, sample size, and advanced topics. Journal of Consumer Psychology, 20, 90–98

Kaplan, D., 2001. Structural equation modeling. In: International Encyclopedia of the Social & Behavioral Sciences, pp. 15215-15222, Elsevier.

Kline, R.B., 2005. Principles and Practice of Structural Equation Modeling (2 Ed). The Guilford Press, New York.

Lei, P-W, Wu, Q., 2007. Introduction to Structural Equation Modeling: Issues and Practical considerations. Educational Measurement: Issues and Practice 26(3), 33-43.

Lu, X., Pas, E.I., 1999. A structural equations model of the relationships among socio-demographics, activity participation and travel behavior. Transportation Research A 31, 1–18.

MacCallum, R.C., Austin, J.T., 2000. Applications of structural equation modeling in psychological research. Annual Review in Psychology, 51, 201-236.

Miranda-Moreno, L.F., Eluru, N., Lee-Gosselin, M., Kreider, T., 2012. Impact of ICT access on personal activity space and greenhouse gas production: evidence from Quebec City, Canada. Transportation 39(5), 895-918.

Ory, D.T., Mokhtarian, P.L., 2009. Modeling the structural relationships among short-distance travel amounts, perceptions, affections, and desires. Transportation Research Part A 43, 26–43

Rai, R.K., Balmer, M., Rieser, M., Vaz, V.S., 2007. Capturing human activity spaces: New geometries. Transportation Research Record 2021, 70-80.

SAS Institute Inc., 2013. SAS/STAT® 13.1 User's Guide. Cary, NC: SAS Institute Inc.

Schönfelder, S., 2001. Some notes on space, location and travel behaviour. In: Proceeding of 1st Swiss Transport Research Conference, Monte Verità / Ascona.

Schönfelder, S., Axhausen, K.W., 2003. Activity spaces: measures of social exclusion? Transport Policy 10, 273–286.

Simma, A., Axhausen, K.W., 2003. Interactions between travel behavior, accessibility, and personal characteristics: the case of upper Austria. European Journal of Transport and Infrastructure Research 3 (2), 79–97.

Sinha, K.C., 2003. Sustainability and urban public transportation. Journal of Transportation Engineering 331–341.

Van Wee, B., Holwerda, H., van Baren, R. 2002. Preferences for Modes, Residential Location and Travel Behaviour: The Relevance of Land-Use Impacts on Mobility. European Journal of Transport and Infrastructure Research 2(3/4), 305-316.

Van Acker, V., Witlox, F., 2010. Car ownership as a mediating variable in car travel behaviour research using a structural equation modelling approach to identify its dual relationship. Journal of Transport Geography 18, 65–74.